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den Butter, F.A.G.; Van de Gevel, F.J.J.S.

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PREDICTION OF THE NETHERLANDS' MONEY STOCK

BY

F.A.G. DEN BUTTER AND F.J.J.S. VAN DE GEVEL*

1 INTRODUCTION

The essential role of the broadly defined money stock (*M2*) in Netherlands' monetary analysis makes close monitoring of future trends in this quantity of the utmost importance. Monetary policy aims at keeping the growth of the money stock in line with the growth of national income so that no inflationary or deflationary tendencies arise. Given the likely, or warranted, course of income, the forecasts for the money stock may indicate whether policy action is needed. Apart from this policy purpose, forecasts for the money stock have a more general use in economic analysis, as this quantity constitutes one of the main macro-economic indicators. One part of the analysis aims at giving short-term forecasts of *M2*. Traditionally, such forecasts are based on projections of the sources of money supply; they are judgemental forecasts for which no formal behavioural model is used. Moreover, these forecasts contain a normative element in that they are closely related to the policy view at the moment the forecasts are made (see Fase, 1986). Future trends in *M2* are also analysed on the basis of the determinants of the demand for money (see, among others, Fase and Kuné, 1974, Den Butter and Fase, 1981, and Huijser, 1987). However, the latter forecasts require assumptions on the future course of national income, the price level, interest rates, inflation and the position of the cycle.

This article provides an operational method for mechanical monthly forecasts of *M2* up to one year ahead, using combined time series models. In the monetary analysis, this mechanical forecast may serve as a yardstick for the above judgemental forecasts. The reason is that the quality of short-term forecasts made by time-series models often surpasses that of forecasts from behavioural models (see Diebold and Pauly, 1987, and for the demand for money Den Butter and Fase, 1980). However, for the medium and long term (say, for predicting a number of years ahead), the behavioural forecast, supplemented with judgemental analysis, offers an advantage in that it may use in-

* Professor of Economics at the Free University, Amsterdam and staff member of the Econometric Research and Special Studies Department of De Nederlandsche Bank NV, Amsterdam, respectively. This study was completed when the first author was at the Nederlandsche Bank. We gratefully acknowledge the useful comments of a referee on a previous version of this article.

formation on the role of equilibrium mechanisms or on predictable structural change.

In any case, for forecasting it is desirable that all relevant information is used, with the constraint that the content of that information outweighs the costs of including it in the forecast. As a consequence, a combination of forecasts often yields a better prediction than each individual forecast (see Makridakis and Winkler, 1983, Mahmoud, 1984, and for a contrary example Holden and Peel, 1986). Bates and Granger (1969) prove that a combination of forecasts makes sense if the individual forecasts are based (to some extent) on mutually independent sources of information. They also show how the weights of the individual forecasts in the combined forecast can be determined. The search for optimal weights in the combination of forecasts has meanwhile been conducted further, by, among others, Newbold and Granger (1974), Granger and Ramanathan (1984), Bopp (1985), and Diebold and Pauly (1986, 1987). The additional information, which makes the use of combined forecasts so fruitful, may relate either to different forecasting procedures (or models) using the same data or to the use of different sources of information, such as the opinions of experts (see Figlewski and Urich, 1983, and Ashton and Ashton, 1985; see also Winkler, 1984). A mixture of these two aspects in the combination of forecasts can be found in the forecasting procedure of the Federal Reserve Board (FRB) where a combination is made both of forecasts of different models and of forecasts at different aggregation levels (monthly and quarterly data, aggregates and components) (see Fuhrer and Haltmaier, 1988, Corrado and Greene, 1988). It must be noted that the forecasting procedure of the FRB specifically aims at utilizing scattered new information on economic developments in the best possible manner.

The combined time series forecast of this article makes use of various sources of disaggregated information on the money stock, *viz.* the breakdown by assets, sources and holdership, and thus shows affinity with the forecasting procedure used at the FRB. In addition to a univariate ARIMA model for the money stock itself, multivariate ARIMA models are built for the components of the money stock for all three ways of disaggregation. With these four ARIMA models, four separate forecasts of *M2* are made every month for one up to twelve months ahead, *i.e.* a total of 48 forecasts. Then the four different forecasts for each month are combined in the best possible manner, the weights changing with the number of months to be forecasted ahead. Thus we obtain a combined forecast for *M2* which is revised every month using the latest data. This guarantees that the forecast is up to date, while the procedure also allows identification of new developments in the movements in the money stock suggested by the information in the latest data.

The next section discusses the data. Section 3 gives the identification and estimates of the individual ARIMA models, whereas section 4 shows the forecasting performance of these individual models. Section 5 deals with the different ways of combining forecasts and selects the most appropriate combination method. Section 6 indicates how the forecasting procedure has been made operational for practical use in policy analysis. Finally, section 7 presents some concluding remarks.

2 DATA

The ARIMA models with which the forecasts are made are estimated with seasonally unadjusted monthly data for the period 1970:1–1987:10. All series have been corrected for breaks in series so that the components of the money stock, when disaggregated in one of the three different ways, always add up to the total series. Moreover, the breaks in series have been corrected in such a way that the 1987 figures for the money stock and the breakdown by assets are in conformity with those published in the 1987 Quarterly Bulletins and Annual Report of the Nederlandsche Bank. Apart from the total series

$M2$: money stock

data are used on the components of $M2$ with regard to

I *Disaggregation by liquid assets*

C: currency
D: demand deposits
TF: time deposits and foreign currency deposits
SGP: short-term government paper with the private sector

with $M2 = C + D + TF + SGP$.

II *Disaggregation by sources of money supply*

NFA: net foreign assets
NMO: net money-creating operations
$PAFD$: public authority floating debt
NMI: net miscellaneous items

with $M2 = NFA + NMO + PAFD - NMI$

III *Disaggregation by holdership*

$M2_h$: $M2$ held by households
$M2_e$: $M2$ held by enterprises
$M2_{inv}$: $M2$ held by institutional investors
$M2_{lg}$: $M2$ held by local government

with $M2 = M2_h + M2_e + M2_{inv} + M2_{lg}$.

The description of *M2* as the sum total of the liquid assets figuring on the balance sheet of the private sector stems from the analysis of the disaggregated demand for money (see Fase, 1979) and from the modelling of the private sector's portfolio behaviour (see, for example, De Nederlandsche Bank, 1985). The disaggregation by sources (or 'causes'), the money stock being broken down by its counterparts in the consolidated balance sheet of the money-creating institutions, forms a traditional element in Netherlands' monetary analysis. It must be noted that this manner of disaggregation of the money stock is not unique to the Netherlands; in Australia it is also used in forecasts of the money stock (see Horne, 1983). Finally, the disaggregation of the money stock by holdership yields the distribution of holdings of *M2* among the various segments of the private sector. For the first two methods of disaggregation, monthly data are available direct from statistical sources (see Table 2.1 in the Quarterly Bulletins of the Nederlandsche Bank). The data used in the disaggregation by holdership are, for the period until 1982:12, mostly synthetic in nature. Moreover, until that period, they were obtained through interpolation of quarterly figures with the aid of the Lisman method (see Boot, Feibes and Lisman, 1967 and Den Butter, Van der Hoeven and Van Loo, 1985, for the method of construction of the quarterly figures). For the subsequent period, most data on the holdership of *M2* are also available on a monthly basis and are, for a major part, based on direct observations (see Jannink, 1986). Although, until 1982, the data on holdership are less reliable than the other data used in this study, we thought it useful to consider them here, as they may as yet contain extra information for the combined forecast of *M2*. The combination weights will show whether this is indeed the case.

Table 1 gives the composition of the money stock in the reference period according to the three ways of disaggregation. It shows that, of the liquid assets, demand deposits made up the largest share of the money stock in the 1970s. At the end of that decade and the beginning of the 1980s, there was a major increase in the share of time deposits. At present, demand deposits and time deposits each make up about 40% of the total money stock. The rest is mainly made up of currency; the share of short-term government paper with the private sector has decreased markedly over the years. In the disaggregation by sources, the position of net money-creating operations presently forms the largest counterpart of the money stock. Net foreign assets accounted for a major proportion especially in the early 1970s. Here, too, the disaggregation by sources shows up the relative decline of short-term government paper with the private sector. When we look at the holdership of *M2*, about half the money supply is traditionally held by the households. The share of the enterprises increased during the observation period from 33% in 1970 to 46% in 1987. Liquidity held by institutional investors, on the other hand, decreased in relative terms in the observation period. The holdership of the local government plays a minor role, but has been included as a residual item.

TABLE 1 – COMPOSITION OF *M2* (AMOUNTS AT END OF YEAR)

	1970		1975		1980		1985		1987	
	billions of guilders	% of total	billions of guilders	% of total	billions of guilders	% of total	billions of guilders	% of total	billions of guilders	% of total
I *Assets*										
Currency	9.3	24.2	13.9	19.2	21.3	19.8	28.6	17.9	33.3	18.8
Demand deposits	17.8	46.2	34.2	47.4	45.4	42.4	62.2	38.9	70.9	40.0
Time deposits and foreign currency deposits	9.1	23.6	22.5	31.2	38.7	36.2	66.5	41.6	72.0	40.6
Short-term government paper with the private sector	2.3	6.0	1.6	2.2	1.7	1.6	2.5	1.6	1.0	0.6
M2	38.5	100.0	72.2	100.0	107.0	100.0	159.8	100.0	177.1	100.0
II *Sources*										
Net foreign assets	16.3	42.3	30.0	41.7	18.1	16.9	43.8	27.4	38.1	21.5
Net money-creating operations	14.1	36.5	38.9	54.0	72.2	67.4	112.5	70.4	127.5	72.0
Public authority floating debt	9.4	24.3	6.7	9.3	23.6	22.1	19.5	12.2	19.8	11.2
Net miscellaneous items	−1.2	−3.1	−3.6	−5.0	−6.9	−6.4	−16.0	−10.0	−8.3	−4.7
M2	38.5	100.0	72.2	100.0	107.0	100.0	159.8	100.0	177.1	100.0
III *Holdership*										
Households	20.7	53.8	35.7	49.5	51.3	47.9	61.9	38.7	76.7	43.3
Enterprises	12.5	32.5	26.6	36.8	44.5	41.6	78.4	49.1	81.6	46.0
Institutional investors	4.9	12.7	8.9	12.3	9.7	9.1	15.8	9.9	15.7	8.9
Local government	0.4	1.0	1.0	1.4	1.5	1.4	3.7	2.3	3.2	1.8
M2	38.5	100.0	72.2	100.0	107.0	100.0	159.8	100.0	177.1	100.0

3 THE ARIMA MODELS

Following the Box and Jenkins (1970) procedure, we first identified and estimated a univariate ARIMA model for total *M2*. The general form of this model is:

$$\phi_p(\mathrm{B})\Delta^d y_t = \theta_0 + \theta_q(\mathrm{B})a_t \tag{1}$$

with y_t the value of the series at time t, a_t a normally distributed stochastic variable, B the lag operator with $\mathrm{B}y_t = y_{t-1}$ and Δ the first difference with $\Delta = 1 - \mathrm{B}$ and thus $\Delta y_t = y_t - y_{t-1}$. Furthermore, θ_0 is a constant, $\phi_p(\mathrm{B}) = 1 - \phi_1\mathrm{B} - \phi_2\mathrm{B}^2 - \dots - \phi_p\mathrm{B}^p$ the AR term of order p, $\theta_q(\mathrm{B}) = 1 - \theta_1\mathrm{B} - \theta_2\mathrm{B}^2 - \dots - \theta_q\mathrm{B}^q$ the MA term of order q and d the degree of differencing needed to transform the series to a stationary one. A model of type (1) is symbolically represented as an ARIMA (p, d, q) model.

An alternative formulation for (1) which concentrates on seasonal series, reads as follows:

$$\phi_p(\mathrm{B})\Phi_P(\mathrm{B}^s)\Delta^d\Delta_s^D y_t = \theta_0 + \theta_q(\mathrm{B})\Theta_Q(\mathrm{B}^s)a_t \tag{2}$$

with s the periodicity of the season ($s = 12$ in the case of monthly data) and $\Phi_P(\mathrm{B}^s)$ and $\Theta_Q(\mathrm{B}^s)$ polynomials in B^s of the order P and Q. Model (2) is written as an ARIMA $(p, d, q) \times (P, D, Q)_s$ model with d the degree of ordinary differencing and D the degree of seasonal differencing, p the number of ordinary autoregressive parameters, P the number of autoregressive seasonal parameters, q the number of ordinary moving-average parameters and Q the number of seasonal moving-average parameters.

The estimation result for the ARIMA model for the money stock, which has been identified as a $(4, 1, 0) \times (0, 1, 1)$ model is given on the first line of Table 2. This model relates to the untransformed money stock, and not to its logarithm, for which we found an ARIMA model with a better fit. Yet, the model with the untransformed data yields better forecasts than the model with the logarithmic transformation. Similar results were obtained for the multivariate models for the liquid assets and the holdership, which are to be discussed below. A logarithmic transformation is not possible in the case of disaggregation by sources, as some series may assume negative values. Therefore, we have based all ARIMA models on untransformed data.

For the components of the money stock, so-called multivariate (seasonal) ARIMA models were built for each of the three different ways of disaggregation. These multivariate ARIMA models, which are sometimes referred to as vector ARIMA models, form the multivariate analogon of equation (1) and are obtained through generalization of that equation. The general form of this model reads:

$$\boldsymbol{\phi}(\mathrm{B})\mathbf{w}_t = \boldsymbol{\theta}_0 + \boldsymbol{\theta}(\mathrm{B})\mathbf{a}_t \tag{3}$$

with $\phi(B)$ an $m \times m$ matrix with polynomials $\phi_{ij}(B)$ of the order p_{ij}; $\theta(B)$ an $m \times m$ matrix with polynomials $\theta_{ij}(B)$ of the order q_{ij}; $\mathbf{w}_t$ an $m \times 1$ vector with elements w_{it} which follow from $w_{it} = \Delta^{d_i} y_{it}$ as a consequence of the desired stationarity; θ_0 is a vector with constants θ_{i0}; the p_{ij}, q_{ij}, $d_i \geq 0$ with i, $j = 1, 2, \ldots, m$, with m the number of time series considered. The $\mathbf{a}_t$ is an $m \times 1$ vector with a_{it} such that $E\mathbf{a}_t = \mathbf{0}$ and $E(\mathbf{a}_t \mathbf{a}_t') = \Sigma_{m \times m}$ the variance-covariance matrix which has its analogon in the regression model. By analogy with the above univariate ARIMA model, the formulation of this multivariate ARIMA model can also be adapted to seasonal series (see Tiao and Box, 1981, Tsay and Tiao, 1984, and Fase, 1985, 1987 for identification, estimation and application of these vector ARIMA models).

The estimation results for the three multivariate models for the components of the money stock are also presented in Table 2, and are indicated as I, II and III. For the sake of uniformity, the identification of the models was based on the same differencing for all series, *viz.* an ordinary differencing and a seasonal differencing ($\Delta\Delta^{12}$). The identification was such that we first identified and estimated a univariate ARIMA model for each separate component. These univariate models were then combined into multivariate models; the pattern of the autocorrelations was used to detect which autoregressive parameters or moving-average parameters lying outside the diagonal in ϕ or θ should possibly be included in the specification of the multivariate model. In the case of the liquid assets, this proves to be an autoregressive parameter of the first order between currency and demand deposits. This outcome is shown on the last line under I. Table 2 shows that in the multivariate model for the sources of *M2*, two cross moving-average parameters of the first order are significant. Finally the multivariate model for disaggregation of the money supply by holdership contains four first-order cross autoregressive parameters. All in all, the relatively small number of significant cross parameters indicates a minor interrelationship between these monetary series. Van der Knoop (1984) comes to the same conclusion in his analysis of multivariate ARIMA models for similar monetary series.

The Box-Pierce test shown in the last column of Table 2 indicates that the estimated ARIMA models generally separate the signal from the noise quite well. According to this test, it is only the model for net money-creating operations which still contains a significant residual pattern. It does turn out, however, that a statistically adequate description of some series requires a number of autoregressive or moving-average parameters of a higher order, which are difficult to interpret from an economic viewpoint.

4 THE FORECASTS WITH THE ARIMA MODELS

The ARIMA models from Table 2 were used to forecast the money stock one to twelve months ahead over the period 1982–1987. In order to imitate as much as possible the forecasting procedure which is set out in section 6, the forecasts

TABLE 2 - ESTIMATION RESULTS FOR ARIMA MODELS (ESTIMATION PERIOD 1970:1-1987:10)

0. Univariate model money stock		
$(1+0.189B^4)\Delta\Delta_{12}M2_t=(1-0.717B^{12})a_t$	$\sigma_a=1.41$	$Q(12)=10.2$
(2.7) (14.1)		
I. Multivariate model assets		
$(1+0.513B-0.463B^3+0.125B^6-0.403B^9)\Delta\Delta_{12}C_t=(1+0.206B)(1-0.753B^{12})a_t$	$\sigma_a=0.20$	$Q(12)=15.4$
(8.3) (9.3) (2.2) (7.6) (2.2) (12.8)		
$\Delta\Delta_{12}D_t=(1-0.656B^{12})a_t$	$\sigma_a=1.00$	$Q(12)=12.4$
(11.9)		
$\Delta\Delta_{12}TF_t=(1+0.156B-0.129B^4)(1-0.783B^{12})a_t$	$\sigma_a=1.35$	$Q(12)=9.6$
(2.3) (1.9) (17.8)		
$\Delta\Delta_{12}SGP_t=(1-0.364B)(1-0.901B^{12})a_t$	$\sigma_a=0.37$	$Q(12)=17.6$
(5.5) (25.7)		
$\phi_{1,C,D}=0.041$		
(2.9)		
II. Multivariate model sources		
$\Delta\Delta_{12}NFA_t=(1+0.159B^2-0.127B^{10})(1-0.601B^{12})a_t$	$\sigma_a=1.04$	$Q(12)=16.3$
(2.7) (1.9) (10.5)		
$\Delta\Delta_{12}NMO_t=(1+0.165B-0.231B^{10})(1-0.818B^{12})a_t$	$\sigma_a=1.20$	$Q(12)=22.2^*$
(2.6) (3.6) (20.0)		
$\Delta\Delta_{12}PAFD_t=(1+0.187B-0.311B^4+0.189B^8-0.104B^{10})(1-0.705B^{12})a_t$	$\sigma_a=1.43$	$Q(12)=14.5$
(3.1) (5.2) (3.0) (1.8) (12.4)		
$\Delta\Delta_{12}NMI_t=(1-0.429B)(1-0.802B^{12})a_t$	$\sigma_a=0.87$	$Q(12)=13.5$
(7.2) (18.2)		

$$\theta_{1,PAFD,NMO} = \underset{(2.0)}{0.146}; \quad \theta_{1,PAFD,NMI} = \underset{(2.1)}{0.202}$$

III. Multivariate model holdership (estimation period 1970:3–1987:9)

$$(1 - \underset{(5.2)}{0.348}\mathrm{B} + \underset{(2.9)}{0.197}\mathrm{B}^4 - \underset{(2.3)}{0.160}\mathrm{B}^6)\Delta\Delta_{12}M2_{h_t} = (1 - \underset{(13.6)}{0.759}\mathrm{B}^{12})a_t \qquad \sigma_a = 0.71 \qquad Q(12) = 17.7$$

$$(1 + \underset{(2.7)}{0.178}\mathrm{B} + \underset{(1.8)}{0.122}\mathrm{B}^4 + \underset{(3.1)}{0.213}\mathrm{B}^7)\Delta\Delta_{12}M2_{e_t} = (1 - \underset{(7.7)}{0.523}\mathrm{B}^{12})a_t \qquad \sigma_a = 1.15 \qquad Q(12) = 5.3$$

$$(1 + \underset{(5.5)}{0.369}\mathrm{B}^4 - \underset{(4.4)}{0.316}\mathrm{B}^7 - \underset{(4.4)}{0.322}\mathrm{B}^{11})\Delta\Delta_{12}M2_{inv_t} = (1 - \underset{(19.2)}{0.866}\mathrm{B}^{12})a_t \qquad \sigma_a = 0.46 \qquad Q(12) = 19.2$$

$$(1 + \underset{(3.4)}{0.246}\mathrm{B}^5 - \underset{(5.5)}{0.401}\mathrm{B}^6)\Delta\Delta_{12}M2_{1g_t} = (1 - \underset{(8.1)}{0.586}\mathrm{B}^{12})a_t \qquad \sigma_a = 0.15 \qquad Q(12) = 17.0$$

$$\phi_{1,M2_h,M2_{inv}} = \underset{(1.8)}{0.174}; \quad \phi_{1,M2_e,M2_{inv}} = \underset{(2.3)}{-0.341}; \quad \phi_{1,M2_e,M2_h} = \underset{(3.6)}{-0.381}; \quad \phi_{1,M2_{1g},M2_h} = \underset{(2.1)}{0.029}$$

Explanatory note: t-values in parentheses; σ_a: standard deviation of the residuals; $Q(12)$: Box-Pierce test of the residual pattern of the disturbances: χ^2 distributed with 12 degrees of freedom with * indicating that the null hypothesis of no residual pattern is rejected; $\phi_{i,x,y}$: ith order cross autoregressive parameter of series x and y; $\theta_{i,x,y}$: ith order cross moving average parameter of series x and y.

have been calculated as follows. The basic starting point being the specification of the models in Table 2, these models were first re-estimated for the period up to and including 1981:12, the reference period being 1970:1–1981:12. On the basis of these estimates, the forecasts from the four different models were subsequently made for 1982:1–1982:12, *i.e.* for one to twelve months ahead. After that, we simulated that the data for January 1982 became available. On the basis of these new data, the forecasts were made, using the models already estimated, for the period 1982:2–1983:1, again imitating an *ex ante* forecast for one to twelve months ahead. After this procedure had been repeated for the months February up to and including November, an annual re-estimation of the ARIMA models was imitated when the figures for December 1982 became available. This means that, for the first time, the forecasts for the period 1983:1–1983:12 were based on estimates up to and including 1982:12. These re-estimations were repeated every year, for five years. The latest *ex ante* forecasts therefore relate to the twelve-month period 1986:12–1987:11, the data for November 1986 and the estimates for the period 1970:1–1985:12 serving as the starting-point.

Thus the forecasts for one to twelve months ahead were obtained for five years, *i.e.* sixty months, using the four different ARIMA models; that means a total of $4 \times 60 \times 12 = 2880$ different forecasts. We introduce the following notation:

$fz_t^{(i)}$: the forecast for time t with model z for i months ahead, thus with $t-i$ as the last observation; $e_t^{(i)} = y_t^{(i)} - y_t$ is the forecast error with $y_t^{(i)} = fz_t^{(i)}$.

The first half of Table 3 presents the root mean square forecast error over the last five years where the *ex ante* forecasts are computed according to the procedure outlined above. As is usual in the case of time series forecasts, the table shows that the average forecast error increases as the forecast is for longer periods ahead. This goes for both the univariate model for *M2* itself, and for the three multivariate models where the forecast for *M2* is obtained through aggregation of the components.

It is noticeable that none of the four models proves to be the best across the board, and that the model yielding the best forecast varies with the number of months forecasted ahead. For example, the best forecast for one month ahead is provided by the multivariate model of the sources. For two up to five months, on the other hand, the univariate model for the money supply gives the best results, while preference should be given to the multivariate model for disaggregation by holdership for six up to ten months. For eleven and twelve months it is again the univariate model which gives the best results. In order to summarize the forecasting performance of the four models in one number, an index was constructed which was set at 100 for the univariate model. The index was obtained by adding up the average forecast errors over the one to twelve months forecasted ahead. According to the index, the forecast made with the

TABLE 3 - ROOT MEAN SQUARE FORECAST ERROR OF *M2*
(IN BILLIONS OF GUILDERS)

Number of months forecasted ahead	0 univariate model	I multivariate model assets	II multivariate model sources	III multivariate model holdership
a over five years (1982–1987)				
1	1.94	1.89	**1.86**	2.11
2	**2.40**	2.48	2.56	2.53
3	**2.69**	2.92	3.01	2.77
4	**2.94**	3.40	3.44	3.20
5	**3.04**	3.48	3.37	3.26
6	3.12	3.47	3.21	**3.12**
7	3.22	3.50	3.24	**3.06**
8	3.26	3.52	3.28	**3.17**
9	3.38	3.67	3.43	**3.11**
10	3.49	3.83	3.60	**3.31**
11	**3.55**	3.95	3.71	3.68
12	**3.60**	4.08	3.76	4.05
index	100	109.65	105.00	102.02
b over the last two years (1985–1987)				
1	2.04	**1.88**	2.04	1.97
2	2.59	2.58	2.75	**2.41**
3	2.89	3.05	3.27	**2.50**
4	2.73	3.12	3.37	**2.40**
5	2.74	3.12	3.35	**2.27**
6	2.82	3.08	3.02	**2.36**
7	2.87	2.96	2.69	**2.53**
8	2.86	2.85	2.55	**2.37**
9	3.01	2.97	2.72	**2.00**
10	3.30	3.41	3.21	**2.27**
11	3.47	3.74	3.55	**2.68**
12	3.40	3.95	3.78	**2.99**
index	100	105.79	104.55	82.90

Explanatory note: the figures in bold indicate which method yields the best forecast, on average, for the corresponding number of months forecasted ahead.

univariate model for *M2* is the most adequate for the five years for which we imitated the forecasting procedure. In that sense, the three ways of disaggregation apparently do not provide useful additional information for the forecast. This observation, *viz.* that the multivariate models themselves offer little or no additional predictive power when compared to the univariate model, is in line with the outcome of Fase (1987), where sophisticated time series models turned out to be no better predictors than the simple time series models. More in general, it is our impression from the empirical literature that the gain offered by multivariate time series models over univariate time series models with respect to predictive performance is very small in the case of (macro)economic data (see also Lütkepohl, 1987).

In most practical cases it is notably the forecasting performance for the recent period which is of importance. Therefore, the second half of Table 3 considers the root mean square forecast error over the last two years. According to this criterion the multivariate model for the holdership gives relatively the best forecasts.

As pointed out above, a fruitful combination of forecasts may need information on the future movements in *M2* in the disaggregated data which is not contained in the data on *M2* itself. In order to obtain a first impression of whether the disaggregated data do contain such other information, in other words, in order to see to what extent the forecast errors differ from one model to another, the correlations of the forecast errors were calculated in Table 4. The table shows that the forecast errors of the multivariate models deviate increasingly from those of the univariate model, as the period to be forecasted ahead lengthens. This is shown by the decreasing values of the correlations in the first three columns of the table. At the beginning of the forecast period, the disaggregation by assets proves to be relatively highly correlated with the univariate forecast. At the end of the forecasting period the specific information content of the disaggregated data, as compared to the aggregated data, is more or less equal for each of the three ways of disaggregation. This is evident from the correlation coefficients in the last lines of the first three columns of Table 4, which are about the same. Finally, it is noteworthy that the forecast errors in the multivariate model for the assets and that for the sources are highly correlated, also if the forecasts are for several months ahead.

5 COMBINATION OF FORECASTS

The question is whether combining the four separate forecasts of the money stock of the previous section can lead to a better predictive performance than that of the four individually. To that end, the best possible use should be made of the additional information contained in the various disaggregated data. Below we give the results of six different combinations, called methods A to F. Most of them have been inspired by the literature mentioned in the introduction, especially Diebold and Pauly (1986, 1987).

Method A describes the combined forecast simply as an unweighted average of the four alternative time series models:

$$y_t^{(i)} = \tfrac{1}{4}(f0_t^{(i)} + fI_t^{(i)} + fII_t^{(i)} + fIII_t^{(i)})$$

TABLE 4 - CORRELATIONS OF THE FORECAST ERRORS (1982-1987)

Number of months forecasted ahead	$\hat{\varrho}$(0,I)	$\hat{\varrho}$(0,II)	$\hat{\varrho}$(0,III)	$\hat{\varrho}$(I,II)	$\hat{\varrho}$(I,III)	$\hat{\varrho}$(II,III)
1	0.96	0.90	0.89	0.90	0.86	0.81
2	0.95	0.86	0.81	0.89	0.79	0.71
3	0.94	0.83	0.72	0.88	0.74	0.68
4	0.89	0.81	0.71	0.90	0.78	0.75
5	0.84	0.77	0.69	0.91	0.79	0.78
6	0.80	0.74	0.69	0.90	0.80	0.80
7	0.75	0.74	0.71	0.91	0.82	0.83
8	0.73	0.73	0.72	0.91	0.83	0.84
9	0.72	0.71	0.72	0.90	0.81	0.80
10	0.70	0.69	0.72	0.90	0.81	0.79
11	0.69	0.68	0.73	0.90	0.81	0.78
12	0.67	0.66	0.71	0.90	0.83	0.79

0 : univariate model for *M2*
I : multivariate model assets
II : multivariate model sources
III : multivariate model holdership

with

$f0_t^{(i)}$: the forecast according to the univariate model for *M2*
$fI_t^{(i)}$: the forecast according to the multivariate model for the assets
$fII_t^{(i)}$: the forecast according to the multivariate model for the sources
$fIII_t^{(i)}$: the forecast according to the multivariate model for the holdership

The other combinations that we tried are based on regression of the realizations with the forecasts of the individual models to be combined. In *method B* the regression is subject to the restriction that the weights must sum to unity:

$$y_t^{(i)} = \hat{\alpha}_0^{(i)} f0_t^{(i)} + \hat{\alpha}_1^{(i)} fI_t^{(i)} + \hat{\alpha}_2^{(i)} fII_t^{(i)} + \hat{\alpha}_3^{(i)} fIII_t^{(i)}$$

with $\hat{\alpha}_0^{(i)} + \hat{\alpha}_1^{(i)} + \hat{\alpha}_2^{(i)} + \hat{\alpha}_3^{(i)} = 1$,

the weights $\hat{\alpha}_z^{(i)}$ having been estimated by the regression

$$y_t = \alpha_0^{(i)} f0_t^{(i)} + \alpha_1^{(i)} fI_t^{(i)} + \alpha_2^{(i)} fII_t^{(i)} + \alpha_3^{(i)} fIII_t^{(i)}$$

The twelve series of weights for method B - one for each number of months to be forecasted ahead - are given in Table 5. The table shows that there are considerable differences in the weights for forecasts of one month ahead and those

TABLE 5 - WEIGHTS OF THE FORECASTS ACCORDING TO THE REGRESSION WITH THE WEIGHTS SUMMING TO UNITY (METHOD B)

Number of months forecasted ahead	0 univariate model	I multivariate model assets	II multivariate model sources	III multivariate model holdership
1	−0.221	0.524	0.598	0.099
2	0.481	−0.098	0.259	0.358
3	0.902*	−0.596	0.216	0.478*
4	0.883*	−0.447	0.135	0.429*
5	0.701*	−0.396	0.296	0.400*
6	0.494*	−0.352	0.422	0.436*
7	0.389*	−0.207	0.318	0.500*
8	0.404*	−0.157	0.342	0.411
9	0.345*	−0.194	0.271	0.578*
10	0.375*	−0.157	0.292	0.490*
11	0.476*	−0.069	0.366	0.227
12	0.556*	−0.041	0.486	−0.002
(mean	0.482	−0.183	0.333	0.367)

Explanatory note: an * indicates that the estimated weight differs significantly from zero at the 5% level.

for longer periods. When forecasting one month ahead, the combined forecast according to method B makes use notably of the information in the multivariate models for the assets and for the sources. In the case of forecasts for more months ahead, it is especially the univariate model and the multivariate model for the holdership which obtain relatively high, positive weights. Nevertheless, in this case, too, the forecast by the multivariate model for the sources remains of importance, albeit not as markedly as in the one-month-ahead forecast. A noteworthy result is the negative weights for the multivariate model of the assets which are incidentally in all cases not significantly different from zero at the 5% level. An explanation may be that forecast errors in the other models are partly offset by the forecast errors with the same sign in the model for the assets. However, this hypothesis is not confirmed by the correlation of the forecast errors, as shown in Table 4, since the forecast errors of the model for the assets are not more highly correlated with the other forecast errors than the forecast errors of the other models among themselves. In their applications, Granger and Ramanathan (1984) apparently, though not expressly, exclude negative weights from their combination formulas. In our case we allow for negative weights as they may neutralize large forecast errors with the same sign.

The restriction that the weights must sum to unity would be met automatically if the individual models were unbiased predictors for each period to be forecast. However, notably in the case of autoregressive models used for forecasting more than one period ahead, this does not hold. Moreover, unbiasedness is not a prime requirement for a predictor. It is more important that the predictor should produce a forecast error with the smallest possible variance (see, for instance, Den Butter, 1975). Consequently, the restriction of weights summing to unity is not necessary for a combined predictor. Against this background, *method C* describes a combined forecast, the weights following from the regression without any restriction. The method is:

$$y_t^{(i)} = \hat{\alpha}^{(i)} + \hat{\alpha}_0^{(i)} f0_t^{(i)} + \hat{\alpha}_1^{(i)} fI_t^{(i)} + \hat{\alpha}_2^{(i)} fII_t^{(i)} + \hat{\alpha}_3^{(i)} fIII_t^{(i)}$$

the weights $\hat{\alpha}^{(i)}$ and $\hat{\alpha}_z^{(i)}$ being estimated from the regression:

$$y_t = \alpha^{(i)} + \alpha_0^{(i)} f0_t^{(i)} + \alpha_1^{(i)} fI_t^{(i)} + \alpha_2^{(i)} fII_t^{(i)} + \alpha_3^{(i)} fIII_t^{(i)}$$

The weights estimated over the forecast period of five years are given in Table 6.

The table shows that, except for the forecast one month ahead, the univariate model has a high positive weight. Notably in forecasts for three to six months ahead, this high weight is offset to a considerable degree by a negative weight for the multivariate model for the assets. The weights of the

TABLE 6 - WEIGHTS OF THE FORECASTS ACCORDING TO THE REGRESSION WITHOUT RESTRICTIONS (METHOD C)

Number of months forecasted ahead	constant term	0 univariate model	I multivariate model assets	II multivariate model sources	III multivariate model holdership
1	3.0	−0.249	0.524	0.614	0.092
2	5.0	0.582	−0.224	0.262	0.349
3	7.8*	1.122*	−0.851*	0.206	0.474*
4	10.3*	1.055*	−0.655*	0.083	0.453*
5	11.6*	0.873*	−0.605*	0.193	0.466*
6	12.5*	0.639*	−0.505*	0.264	0.523*
7	13.7*	0.519*	−0.341	0.138	0.596*
8	14.5*	0.577*	−0.301	0.187	0.445*
9	16.3*	0.558*	−0.315	0.147	0.507*
10	18.3*	0.656*	−0.261	0.186	0.304
11	22.1*	0.847*	−0.223	0.302	−0.063
12	26.2*	0.968*	−0.256	0.423	−0.297
(mean	13.4	0.679	−0.334	0.250	0.321)

Explanatory note: an * indicates that the estimated weight differs significantly from zero at the 5% level.

multivariate model for the sources and of the multivariate model for holdership vary considerably, depending on the number of months forecasted ahead, but are mostly positive. It is noteworthy that the constant term increases as more months must be forecasted ahead. This could suggest that the bias of the predictors for the individual models increases as the forecasting horizon becomes more distant. The majority of the negative weights does not differ significantly from zero.

The above methods use fixed weights in combining the forecasts, albeit that the weights vary with the number of months forecasted ahead. It is, however, conceivable that the importance of the forecasts by one of the individual models may increase or decrease over time. Therefore, we have tried the following methods, in which the weights vary over time. The first is *method D*, which describes a trend-based change in the weights. The combined forecast is:

$$y_t^{(i)} = \hat{\alpha}^{(i)} + \hat{\beta}^{(i)}t + \hat{\alpha}_0^{(i)} f0_t^{(i)} + \hat{\beta}_0^{(i)} t f0_t^{(i)} + \hat{\alpha}_1^{(i)} fI_t^{(i)} + \hat{\beta}_1^{(i)} t fI_t^{(i)} + \hat{\alpha}_2^{(i)} fII_t^{(i)} + \hat{\beta}_2^{(i)} t fII_t^{(i)} + \hat{\alpha}_3^{(i)} fIII_t^{(i)} + \hat{\beta}_3^{(i)} t fIII_t^{(i)}$$

with coefficients $\hat{\alpha}^{(i)}$, $\hat{\beta}^{(i)}$, $\hat{\alpha}_z^{(i)}$ and $\hat{\beta}_z^{(i)}$ estimated by the regression:

$$y_t = \alpha^{(i)} + \beta^{(i)}t + \sum_{z=0,\mathrm{I},\mathrm{II},\mathrm{III}} \{\alpha_z^{(i)} fz_t^{(i)} + \beta_z^{(i)} t fz_t^{(i)}\}$$

The estimated coefficients for method D for the period 1982–1987 are given in Table 7. Considering that the trend coefficients describe the change in the weights from one month to the next, the results in Table 7 show that in a number of cases there are major shifts in the weights. Moreover, the weights again vary widely with the number of months to be forecasted ahead, and the large number of coefficients which are not significant at the 5% level suggests great uncertainty and instability as to the direction in which the weights change.

Diebold and Pauly (1987) found that, in the calculation of the optimum weights for combined forecasts, forecast errors in the more distant past are less important than the most recent forecast errors. In line with these authors, we have tested variants of methods B and C using generalized least squares regression, where the more recent observations acquire increasing weights. However, in our case these variants do not produce results which increase predictive performance. Moreover, we might have tried variants of the (trend) regressions with different weights from year to year for each specific month of the year. We did not do so because the ARIMA models implicitly describe the seasonal patterns of the time series so that it should not matter to which specific month of the year the forecast relates. Whether this is the case in practice may be a point for future research.

Yet, as an alternative we tried with some success a combined forecast which relates the change in the weights to the forecasting quality of the individual models in the recent past. *Method E* uses an indicator of the quality of the re-

TABLE 7 - WEIGHTS OF THE FORECASTS ACCORDING TO THE REGRESSION WITH A TREND (METHOD D)

Number of months fore-casted ahead	constant term	trend	0 univariate model		I multivariate model assets		II multivariate model sources		III multivariate model holdership	
	α	β	constant weight α_0	trend weight β_0	constant weight α_1	trend weight β_1	constant weight α_2	trend weight β_2	constant weight α_3	trend weight β_3
1	9.0	0.2	0.783	−0.031	−2.175	0.082*	2.184*	−0.051	0.130	−0.002
2	13.4	0.3	1.414	−0.032	−1.898	0.054	0.900	−0.020	0.473	−0.003
3	17.2	0.5*	2.013*	−0.031	−2.417*	0.044	0.782	−0.019	0.482	0.003
4	6.9	0.5*	1.494*	−0.015	−2.031*	0.042*	1.041	−0.032	0.443	0.002
5	−2.6	0.7*	0.922*	−0.001	−1.475*	0.026	1.279	−0.035	0.298	0.005
6	7.8	0.5*	0.550	0.003	−0.928	0.012	0.730	−0.014	0.591	−0.004
7	32.1	0.3	0.286	0.001	−0.432	0.001	−0.230	0.018	1.132*	−0.022
8	32.8	0.3	0.282	0.004	−0.133	−0.008	−0.405	0.027	1.007*	−0.024
9	20.9	0.2	0.604	−0.003	−0.256	−0.002	−0.235	0.014	0.742	−0.010
10	22.7	0.3	0.903	−0.009	0.243	−0.016	−0.345	0.019	0.042	0.005
11	30.9*	0.2	1.338*	−0.018	1.108*	−0.047*	−1.091	0.050*	−0.567	0.014
12	32.3*	0.4	1.099*	−0.008	0.771	−0.036*	−0.356	0.029	−0.737*	0.013

Explanatory note: an * indicates that the estimate differs significantly from zero at the 5% level.

cent forecast based on the ratio of the forecast error of an individual forecast to the sum of the forecast errors for all four individual forecasting models. This quality indicator for the forecast for i months ahead is calculated as:

$$Gz_t^{(i)} = \frac{1}{(y_{t-i}-fz_{t-i}^{(i)})^2} \Big/ \left(\sum_{q=0,\mathrm{I},\mathrm{II},\mathrm{III}} \left(\frac{1}{(y_{t-i}-fq_{t-i}^{(i)})^2} \right) \right)$$

$$\text{for } z = 0,\ \mathrm{I},\ \mathrm{II},\ \mathrm{III}$$

For an individual model this quality indicator increases as the model gives better forecasts of the most recent realizations. It sums to unity over the individual models. The combined forecast using this indicator is:

$$\begin{aligned} y_t^{(i)} &= \hat{\alpha}^{(i)} + \hat{\alpha}_0^{(i)} f0_t^{(i)} + \hat{\beta}_0^{(i)} G0_t^{(i)} f0_t^{(i)} + \hat{\alpha}_1^{(i)} fI_t^{(i)} + \hat{\beta}_1^{(i)} GI_t^{(i)} fI_t^{(i)} \\ &+ \hat{\alpha}_2^{(i)} fII_t^{(i)} + \hat{\beta}_2^{(i)} GII_t^{(i)} fII_t^{(i)} + \hat{\alpha}_3^{(i)} fIII_t^{(i)} + \hat{\beta}_3^{(i)} GIII_t^{(i)} fIII_t^{(i)} \end{aligned}$$

with coefficients $\hat{\alpha}^{(i)}$, $\hat{\alpha}_z^{(i)}$ and $\hat{\beta}_z^{(i)}$, estimated by the corresponding regression. The expected sign of coefficients $\hat{\beta}_z^{(i)}$ is positive, since this would cause an individual model which performs well for the recent past to acquire a high weight in the combined forecast at that moment. Most estimates of coefficient $\hat{\beta}_z^{(i)}$ indeed prove to be positive, although in a number of cases they also assume negative values, which would not appear plausible.

In *method* F, a variant of method E, the quality indicator was calculated not on the basis of the most recent forecast error known but on that of the sum of the most recent forecast errors known for a period of one year. In this case the quality indicator is:

$$Hz_t^{(i)} = \frac{1}{(\frac{1}{12}) \sum_{j=0}^{11} (y_{t-i-j}-fz_{t-i-j}^{(i)})^2}$$

$$\Big/ \left(\sum_{q=0,\mathrm{I},\mathrm{II},\mathrm{III}} \left\{ \frac{1}{(\frac{1}{12}) \sum_{j=0}^{11} (y_{t-i-j}-fq_{t-i-j}^{(i)})^2} \right\} \right)$$

$$\text{where } z = 0,\ \mathrm{I},\ \mathrm{II},\ \mathrm{III}$$

and the combined forecast of method F is analogous to that of method E with $Hz_t^{(i)}$ instead of $Gz_t^{(i)}$. It is noteworthy that the estimates of coefficient $\hat{\beta}^{(i)}$ now very frequently assume negative instead of the expected positive values. This is not very plausible and makes the adequacy of this combined forecast doubtful.

The first half of Table 8 presents the root mean square forecast errors of the combination methods A to F for the five years of the forecast period and confronts them with the same measure of the forecast errors in the univariate model. These results show that, measured by the general index, all combined forecasts discussed above perform better here than the univariate model (this is, incidentally, the intention: methods of combination whose performance falls short of that of the univariate model have been left out of consideration in the foregoing). For method A, the unweighted average, which produces the smallest gain in predictive power, the gain is still noteworthy, because, as is shown in Table 3, the multivariate models themselves do not match the performance of the univariate model. Apparently, the information content provided by the three different ways of disaggregation is still sufficient to achieve an improvement in the performance of the combined forecast. For method B, with the fixed weights estimated by regression and summing to unity, the gain in predictive power compared with the univariate model is about 10%. According to the general index, the combined forecast by method C, with weights from non-restricted regression, leads to an improvement of nearly 25%. In this case, it is noteworthy that the forecast errors do not increase with the number of months to be forecasted ahead. The same phenomenon is evident for methods D, E and F. This may be related to the fact that the constant term becomes larger with the number of months to be forecasted ahead and therefore that the importance of the ARIMA model forecasts in the combined forecast decreases with the number of months to be forecasted ahead. According to the general index, the performance of methods D, E and F is roughly the same. The gain in predictive power is about 30%. It must, however, be noted that these percentages overstate reality to some extent as the estimates of the weights cover the same period as the calculation of the forecast error. This bias is stronger as the number of weights to be estimated increases.

The second half of Table 8 presents the root mean square forecast errors for the last two years of the forecast period. Generally, no big differences occur as compared with the results for the whole forecast period of five years discussed above. However, measured by the general index, the regression with the trend (method D) now proves to perform best.

In summary, methods D, E and F prove the best for combining the forecasts if the general index from Table 8 is used as the criterion. In that respect, these methods with variable weights are to be preferred to the methods using fixed weights. The implication would be that the additional information content which the different ways of disaggregation offer to the forecasts may differ from one period to the next. However, closer analysis of the individual forecast errors shows that combination methods C to F, which are not subject to the restriction that the weights of the individual methods should sum to unity, often generate forecasts outside the range of the individual forecasts. Table 9 shows the relevant percentages. Although the realizations are frequently outside this range as well – in that case the individual forecasts are all too high or too low – this characteristic appears to make combination methods C to F less suitable in the event that the individual forecasts produce plausible values in relation to the notion on future developments in nominal income whereas the combined forecasts do not. This is true of the use of the combined forecasts in

TABLE 8 – ROOT MEAN SQUARE FORECAST ERROR OF *M2*
(IN BILLIONS OF GUILDERS)

Number of months forecast ahead	0 uni-variate model	A average	B regression with restriction	C regression without restriction	D regression with trend	E regression with indicator of quality, not lagged	F regression with indicator of quality, lagged
a for five years (1982–1987)							
1	1.94	1.87	1.83	1.78	1.62	**1.61**	1.71
2	2.40	2.33	2.32	2.23	2.10	2.17	**2.10**
3	2.69	2.63	2.48	2.30	**2.10**	2.21	2.20
4	2.94	3.00	2.77	2.49	2.30	2.35	**2.26**
5	3.04	3.03	2.84	2.51	2.33	**2.32**	2.39
6	3.12	2.95	2.81	2.44	2.30	2.30	**2.30**
7	3.22	2.97	2.86	2.44	2.28	2.21	**2.18**
8	3.26	3.01	2.93	2.48	2.32	**2.20**	2.29
9	3.38	3.07	2.93	2.39	2.32	**2.23**	2.25
10	3.49	3.20	3.08	2.46	2.36	2.25	**2.24**
11	3.55	3.33	3.23	2.41	2.11	2.09	**2.05**
12	3.60	3.45	3.26	2.10	1.82	1.91	**1.80**
index	100	95.12	90.97	76.48	70.87	70.60	70.30

b for the last two years (1985–1987)							
1	2.04	1.93	1.92	1.88	**1.66**	1.78	1.78
2	2.59	2.49	2.48	2.40	2.08	2.42	**2.00**
3	2.89	2.81	2.68	2.57	**1.95**	2.54	2.42
4	2.73	2.73	2.48	2.25	**1.61**	2.08	2.22
5	2.74	2.68	2.49	2.11	**1.48**	2.02	2.24
6	2.82	2.60	2.46	2.01	**1.62**	1.93	2.25
7	2.87	2.55	2.48	2.03	**1.57**	1.74	2.08
8	2.86	2.44	2.38	1.91	**1.65**	1.87	1.75
9	3.01	2.45	2.21	1.72	1.57	1.87	**1.54**
10	2.30	2.83	2.59	2.10	1.86	2.14	**1.65**
11	3.47	3.13	3.09	2.43	2.11	2.01	**1.61**
12	3.40	3.29	3.35	2.30	2.02	2.14	**1.56**
index	100	91.97	88.17	74.09	60.96	70.70	66.59

Explanatory note: The figures in bold indicate which combination method yields the best forecast, on average, for the corresponding number of months forecasted ahead.

TABLE *9* – PERCENTAGES OF THE COMBINED FORECASTS OUTSIDE THE RANGE OF THE INDIVIDUAL FORECASTS (PERIOD 1982-1987)

Number of months forecast ahead	A average	B regression with restriction	C regression without restriction	D regression with trend	E regression with indicator of quality, not lagged	F regression with indicator of quality, lagged	realization
1	0.0	13.3	40.0	58.3	50.0	51.7	73.3
2	0.0	1.7	26.7	56.7	30.0	36.7	76.7
3	0.0	16.7	30.0	56.7	38.3	53.3	65.0
4	0.0	20.0	38.3	58.3	48.3	51.7	68.3
5	0.0	5.0	35.0	50.0	50.0	48.3	63.3
6	0.0	5.0	36.7	45.0	43.3	41.7	61.7
7	0.0	1.7	36.7	40.0	46.7	55.0	75.0
8	0.0	0.0	36.7	45.0	46.7	55.0	75.0
9	0.0	1.7	40.0	40.0	50.0	45.0	68.3
10	0.0	1.7	43.3	46.7	51.7	46.7	60.0
11	0.0	0.0	43.3	48.3	51.7	46.7	55.0
12	0.0	1.7	41.7	55.0	48.3	38.3	55.0
all months	0.0	5.7	37.4	50.0	46.3	47.5	66.4

1988, as described in the next section, so that in this event method B is recommended.

6 THE FORECASTING PROCEDURE

The analysis in the previous sections has led us to design the following operational forecasting procedure for monthly forecasts of the money stock up to twelve months ahead. The forecasts are to be made each month as soon as new data become available. It is noted that monetary data become available with a lag of about two months, so that the one and two month forecasts actually relate to the immediate past.

The forecasting procedure consists of the following stages:

1. Upon receipt, the new data are immediately added to the existing data and, where necessary, are adjusted for breaks in series. This may also entail changes in provisional data for past months.
2. Using the current versions of the individual ARIMA models, four new forecasts of *M2* are generated on the basis of the new database.
3. Using the combination formulas discussed above, with the current weights, the four different forecasts are combined into a single forecast. This is done both by method B, which is currently preferred, and by the other combination methods.
4. Once a year, upon receipt of the December data, the four ARIMA models are re-estimated and, where necessary, re-specified. The new estimates are used for forecasts throughout the whole next year.
5. Moreover, upon receipt of the December data, the weights of the combination formulas of methods B to F are re-estimated over a forecast period of the past five years. Again, these new weights are used for combining the forecasts throughout the next year. At the same time, the quality of the forecasts for the past period is analysed to ascertain whether the preferred method of combination is still the best or whether it should be replaced by another method.

The resulting forecasts of the money stock can be presented each month in the format of Table 10. The table relates to the situation after receipt of the data for December 1987 and, hence, presents the forecasts for the period 1988:1 to 1988:12. In addition to the forecasts generated by the preferred combination method, the table also includes the results of the other combination formulas so as to judge their plausibility and to enable *ad hoc* decisions to adopt a different combined forecast. It shows that the forecasts generated by methods C to F, in which the combination weights do not sum to unity, prove to be considerably below the range of the individual forecasts for the relevant forecasting period of the table. Especially the forecasts produced by method D with trend regression, which had proved to perform so well for the period 1982–1987 as measured by the mean square forecast error (see Table 8), now lead to implausibly low values. This shows that a technical selection of the

TABLE 10 - MONTHLY FORECASTS OF THE MONEY STOCK (BILLIONS OF GUILDERS)

	most recent obser-vation 1987:12	forecasts 1988:1	1988:2	1988:3	1988:4	1988:5	1988:6	1988:7	1988:8	1988:9	1988:10	1988:11	1988:12	% growth on an annual basis
0 Univariate model money stock	177.1	176.9	179.2	183.0	185.6	189.4	188.7	186.2	184.3	184.9	185.7	186.7	186.0	5.0
I *Multivariate model assets*														
Currency	33.3	33.0	33.0	33.4	33.9	34.2	34.7	34.9	34.6	35.1	35.1	35.3	36.3	
Demand deposits	70.8	70.9	70.9	71.3	72.9	77.4	77.4	75.2	73.3	74.4	74.2	75.0	74.9	
Time deposits and foreign-currency deposits	72.0	72.6	74.5	77.2	78.4	77.2	76.5	76.3	76.3	76.0	76.5	76.7	75.7	
Short-term government paper with the private sector	1.0	0.7	0.8	1.1	1.0	1.1	1.0	0.9	1.2	1.2	0.9	0.8	0.8	
M2	177.1	177.2	179.2	183.0	186.2	189.9	189.6	187.3	185.4	186.7	186.7	187.8	187.7	6.0
II *Multivariate model sources*														
Net foreign assets	38.1	39.0	40.5	41.3	40.6	44.5	43.6	42.8	42.1	41.0	41.3	41.2	39.6	
Net money-creating operations	127.5	127.8	129.0	129.0	130.7	131.1	131.3	131.2	130.2	131.5	133.4	133.5	135.3	
Public authority floating debt	19.8	19.5	18.4	20.8	22.5	22.2	23.6	21.3	20.1	20.7	20.1	20.6	20.0	
Net miscellaneous items	8.3	8.7	8.2	7.2	7.6	6.8	7.6	7.5	7.1	8.2	8.9	8.4	8.9	
M2	177.1	177.6	179.7	183.9	186.2	191.0	190.9	187.8	185.3	185.0	185.9	186.9	186.0	5.0

III *Multivariate model holdership*														
M2 held by households	76.7	77.0	77.5	77.9	79.0	81.7	82.0	81.3	80.7	80.7	80.8	81.4	81.6	
M2 held by enterprises	81.5	79.8	82.1	85.7	87.7	90.0	88.9	86.2	84.3	84.6	85.0	85.6	84.5	
M2 held by institutional investors	15.7	16.2	16.3	15.7	15.4	15.1	15.2	15.6	16.2	16.5	16.5	16.2	16.3	
M2 held by local government	3.2	2.5	2.1	2.1	2.2	2.2	2.6	2.4	2.4	2.4	2.5	2.5	3.0	
M2	177.1	175.5	178.0	181.4	184.3	189.0	188.7	185.5	183.6	184.2	184.8	185.7	185.4	4.7
Combined forecast generated by:														
- preferred combination method														
method B	177.1	177.3	178.9	182.4	184.9	189.7	189.3	186.1	184.2	184.2	185.2	186.5	185.8	4.9
- other methods														
method A	177.1	176.8	179.0	182.8	185.6	189.8	189.5	186.7	184.7	185.2	185.8	186.8	186.3	5.2
method C	177.1	177.0	178.4	181.3	183.1	187.0	186.4	182.9	181.4	181.3	182.2	183.1	181.8	2.7
method D	177.1	161.8	180.3	170.5	180.8	168.1	183.8	170.5	181.9	181.5	185.3	177.4	175.4	−1.0
method E	177.1	177.4	178.1	180.9	182.7	186.7	186.1	181.4	181.2	180.8	182.8	184.6	183.7	3.7
method F	177.1	176.6	177.9	178.4	181.0	185.0	186.0	185.6	180.2	180.4	181.3	182.1	180.0	1.6

forecasting method by a criterion representing past predictive performance should be supplemented with a plausibility check based on judgment.

In order to distinguish to what extent the changes in the forecasts based on the December data, as compared to the forecasts in November, are caused by the new information for this month and to what extent the forecasts change because of the new estimates of the ARIMA models, the new combining weights and/or another combination method, the December forecasts are to be presented in two parts using the format of Table 10: one containing the new forecasts based on the old estimates and combination formula and the other containing the updated forecasts based on the re-estimated ARIMA models and combination weights. In fact, the choice for re-specifying and/or re-estimating the models and combination weights once a year is rather arbitrary and we have not investigated whether a more frequent repetition of the procedure would pay off in terms of an increase in predictive performance. Apart from the trade-off with respect to manpower, there is a trade-off between stability for the sake of interpretation of the results and accuracy, much the same as with yearly seasonal adjustment of economic time series *versus* concurrent adjustment. We believe that a yearly re-specification and re-estimation is adequate.

Finally we mention that the forecasts of Table 10 include the seasonal pattern in *M2* and its components. This is the consequence of the fact that the ARIMA models are, and should be, specified and estimated using original, seasonally unadjusted data, as these models are specifically equipped for description and hence prediction of seasonal time series. In the case that forecasts of *M2* without seasonality are needed, the forecasts of Table 10 can be combined with the corresponding observations over the past and be seasonally corrected with the relevant adjustment method.

7 CONCLUDING REMARKS

This paper describes monthly forecasting of the money stock for up to twelve months ahead using combined ARIMA models. In addition to time series data of the money stock itself, this procedure uses the information contained in the disaggregation of the money stock into liquid assets, sources of money supply and holdership. For these three ways of disaggregation, multivariate ARIMA models were specified and estimated; in each case, the forecast of the money stock is calculated as the sum of the forecasted components. A simulation of the forecasting procedure for the period 1982–1987 shows that, if we look at the results of the individual forecasts generated by the multivariate ARIMA models, the additional information provided by the disaggregated data is not substantial. Despite the fact that the univariate ARIMA model of the money stock performs better than the multivariate ARIMA models for the components, some gain in predictive power may be achieved by a suitable combination of the individual forecasts. Ultimately, on the basis of the plausibility of the results, that method of combination was chosen in which the weights of the individual forecasts result from a regression subject to the restriction that these weights sum to unity. Although, measured by the mean square forecast error, greater gains for the forecast period were achieved using combination methods which do not meet this restriction, these methods failed to generate plausible results for the most recent period.

Thus an operational forecasting procedure results whose merits will have to be tested in practice and which will have to be evaluated from time to time. The procedure may be extended and polished in various ways. For instance, it is conceivable to combine the mechanical time series forecast with subjective forecasts of the money stock using the same methodology of combination described above. Additionally, it is possible to combine the forecasts with forecasts of a multivariate ARIMA model (or, as a simple alternative, a *VAR* model) describing the relationship between the money stock and other major macro-economic data which become available on a monthly basis, such as personal consumption, manufacturing output, prices, interest rates and a cyclical indicator. Furthermore, the monthly forecasts may be combined with forecasts of *M2* on a quarterly basis generated by a macro-economic policy model (*e.g.* MORKMON). Finally, we note that it would be possible to reconcile the forecasts of the components of the money stock, which are generated by the individual multivariate ARIMA models, with the forecast of the money stock as generated by the preferred method of combination. In designing the above procedure we aimed solely at the best mechanical forecast of the total money stock and not at that of its components.

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Summary

PREDICTION OF THE NETHERLANDS' MONEY STOCK

This article describes the operational procedure for a mechanical monthly forecast of the money stock in The Netherlands for up to twelve months ahead. In addition to time series data of the money stock itself, the procedure uses the information provided by the disaggregation of the money stock into financial assets, sources of money supply and holdership. The forecast from a univariate ARIMA model of the money stock is combined with three different forecasts from vector ARIMA models for the components distinguished by the three ways of disaggregation. The combination weights, which differ for each number of months to be forecasted ahead, are determined by regression analysis.